BIDIRECTIONAL ANALYSIS MODEL OF GREEN INVESTMENT AND CARBON EMISSION BASED ON LSTM NEURAL NETWORK

by

Yiguo HU *

Business School of Xiangtan University, Xiangtan, China

Original scientific paper
https://doi.org/10.2298/TSCI221201033H

Clarifying how the green investment alleviates carbon emissions paves the way for achieving carbon peak and carbon neutralization at a faster pace. In order to propose an effective evaluation model and analyze the interaction between green investment and total carbon emissions, we first and foremost collected data from 30 provinces in China from 2007 to 2019. Secondly, we introduced long short-term memory (LSTM) neural network model, with the amount of government investment in pollution control and environmental infrastructure construction as the model input variables. We also select the total amount of carbon emissions as the model output variables to obtain a neural network model with multiple inputs and a single output, which can effectively analyze the potential relationship between green investment data and the total amount of carbon emissions data. Then, the OLS model is introduced to test the relationship obtained by LSTM neural network model and analyze its robustness. As a result, the experiment indicates that the LSTM network conceived by us has reliable robustness and fitting performance, with green investment positively affecting total carbon emissions. Meanwhile, we give corresponding policy recommendations according to the model results.

Key words: *LSTM neural network model, OLS model, green investment, total carbon emissions*

Introduction

Ever since the Industrial Revolution, social products have abounded, giving considerable improvements to human life in material thanks to industrial productions. By the same token, the demand for natural resources for human production and living activities is on the rise day by day, emitting plentiful greenhouse gases, with CO_2 as the majority, which eventually harms the ecological environment on earth. Nowadays, in addition to the ecological environment, political, economic, social, resource, and other fields are all stained by GHG emissions, which have deteriorated into a major practical problem hindering human survival and development. Reflecting on the traditional development mode, people realize the necessity of mitigating the negativity of human activities on ecology. Countries all over the world have embarked on decreasing GHG emissions by all means to undercut the greenhouse effect on our living environment. It's worth noting that with the increasingly prosperous economic growth in

*Author's e-mail: Yiguo_Hu@hotmail.com

the future, global carbon dioxide emissions will keep increasing for some time. In addition to variations in population, resource demand, technical advances, and economic development among worldwide countries, there is still a long way to go to lessen GHG emissions and alleviate ecological deterioration. Public investment in the form of green finance is pivotal to mitigating GHG emissions, adjusting energy structure, and stabilizing the climate environment. Therefore, to meet the increasing demand for low-carbon projects, countries need to deploy appropriate strategies and use green financial tools to meet climate challenges. Green investment, as a financial tool to promote the development of a circular economy through investment, is crucial to promote environmental protection and economic growth in a co-ordinated manner. Meanwhile, how to use this powerful engine of reducing carbon emissions to actualize a win-win prospect between ecological protection and economic growth has become a vital topic.

Recently, broad applications can be seen in artificial intelligence in various fields, which can be regarded as a feature extractor or a function approximator. The interaction fitting between green investment and total carbon emissions can be deemed as a forecasting model, that is, the future trend can be predicted through the relationship between historical green investment and total carbon emissions, so as to guide the current policy-making and research. Traditional prediction models are all statistical or linear methods. Because of their fast calculation and relatively stable performance, they have been the focus of research for a long time. The more common models are autoregressive integrated moving averages [1-3], exponential smoothing [4], multiple linear regression, [5], and so on. The linear methods are difficult to face non-linear problems, especially when the data is unstable and the trend is not obvious. Even in general situations, these simpler models still have the insufficient performance to extract complex data and make accurate predictions.

As for machine learning and neural network models, many classical algorithms have been proven to be more effective methods in dealing with prediction problems. Support vector machine (SVM) is deemed as a widely used model, which was originally used in the classification algorithm, but was used in regression problems in the prediction field. Chen *et al.* [6] have achieved impressive results via the SVM model. With in-depth exploration, its research focus often lies in how to select model parameters. Mayur Barman *et al.* [7] proposed to combine SVM with the grasshopper optimization algorithm to estimate suitable parameters. In addition, the convolution neural network (CNN) is also a favorite model of researchers for a long time. Kuo *et al.* [8] used the classical CNN algorithm to construct three convolution layers and three pooling layers, predicting the next three days after learning the data of the past seven days. Simple neural networks are difficult to obtain the temporal correlation of sequence data, so networks that can extract the temporal information of sequence, such as recurrent neural networks (RNN), are used for prediction. Wang *et al.* [9] adopts LSTM, whose difference is that the traditional point prediction is extended to quantile probability prediction by guiding parameter training with pinball loss instead of mean square errors, making it stand out among many LSTM-based network models. However, information premised on ordinary LSTM is transmitted in one direction, so you can only use the information of the past.

To consider the two-way information of the past and the future at the same time, He *et al.* [10] put forward a bi-directional LSTM (Bi-LSTM) neural network which adds weight distribution and extraction of effective features to make full use of current known data for prediction. This not only makes use of past load information and considers future load information, but also has higher prediction accuracy and better generalization ability. Because traditional point prediction can't solve the generalization of uncertain information for each timestamp, probabilistic forecasting is proposed to meet such challenges. In addition to the quantile prediction previously mentioned (a kind of probabilistic forecasting), there are other more effective methods with more extensive usage. The quantile regression neural network (LASSO-QRNN) proposed by He *et al.* [10] evaluated the forecasting of electricity consumption against various quantiles in the near future by extracting important features from the external factors that affect the electricity consumption forecast. Zhang *et al.* [11] proposed an improved QRNN (iQRNN) to solve low efficiency, high cost, and easy over-fitting of traditional QRNN, which introduced the popular technology in deep learning to comprehensively optimize its all-round performance. The memory networks tend to fall into the performance degradation caused by gradient disappearance, explosion, and information loss when facing long-time series. Researchers put forward residual networks to solve such problems. Premised on the power load forecasting in short term of the deep residual network, Li *et al.* [12] used a neural network with the basic structure and optimized residual network as well as an integration strategy to perfect its old short-term prediction.

Model framework

So far, the research on the mentioned relationship is still in its infancy. From the definition of green investment, some scholars see green investment as an important tool for reducing GHG and carbon emissions [12, 13] and key to improving the capacity of ecologically sustainable economic systems [14]. Others consider green investments as investments in traditional hydropower, pollution abatement, and carbon sequestration [15].

According to the existing research on the interaction between them, most scholars regard green investment as the catalyst to mitigate carbon emissions and guide production in a green and low-carbon way [14, 16, 17]. The negative correlation between green investment and productive carbon emissions validly controls the uprising carbon emissions resulting from production [18]. From the perspective of agriculture, such a restraining relationship exists in both the short and long term. Besides, promoting green investment benefits agricultural carbon emissions m itigation [19]. Meanwhile, the government can also reduce CO_2 emissions by putting more investments in energy development and studies, so as to improve environmental quality and promote sustainable economic development. Therefore, we believe that a strong connection between green investment and carbon emissions can be witnessed based on the above investigations. To extract the aforementioned potential relationship more efficiently, with 30 provinces in China from 2007 to 2019 as research samples, this paper proposes an effective LSTM neural network model to research such a fuzzy relationship and verifies the feasibility of LSTM neural network model by constructing an OLS model between green investment and carbon emissions.

The LSTM neural network

The interaction fitting between green investment and total carbon emissions can be regarded as a prediction model. As an effective prediction model, the LSTM network shown in fig. 1 well overcomes the gradient explosion and gradient disappearance caused by the traditional RNN neural network model in the gradient propagation. The LSTM neural network is poles apart from the traditional feedforward neural network. As a sequence-based model, LSTM neural network can establish a temporal correlation between the previous signal and the current situation, which signifies that the decision made at time, $t - 1$, may be the model decision to affect t after t. It has the following advantages:

- a *gate mechanism* is designed for each neuron cell to retain the useful information in the long-term storage process, which is equivalent to a *soft* switch and

– a deep learning neural network belongs to a recursive category, that is, data will expand according to time series and historical data will have an impact on future data, which makes LSTM neural network suitable for learning data with time series characteristics.

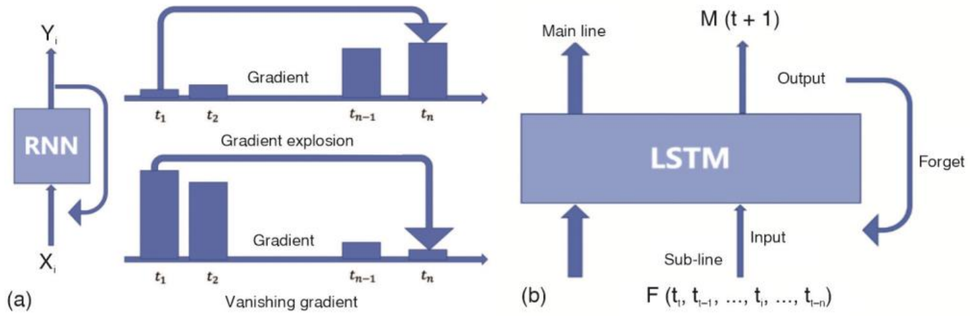

Figure 1. Comparison of (a) RNN and (b) LSTM

You can use the following functions to model hidden layer neurons, where x_t represents green investment and o_t represents carbon emission reduction:

$$i_t = \sigma\left(w_i\left[h_{t-1}, x_t\right] + b_i\right) \tag{1}$$

$$f_t = \sigma\left(w_f\left[h_{t-1}, x_t\right] + b_f\right) \tag{2}$$

$$c_t = \tan h(w_{\tilde{c}}\left[h_{t-1}, x_t\right] + b_{\tilde{c}}) \tag{3}$$

$$c_t = f_t c_{t-1} + i_t c_t \tag{4}$$

$$o_t = \sigma\left(w_o\left[h_{t-1}, x_t\right] + b_o\right) \tag{5}$$

$$h_t = o_t \tan h(c_t) \tag{6}$$

where f_t, i_t, o_t are the output values of the forgetting gate, input gate, and output gate, respectively. The output value h_t of the LSTM hidden layer and the input data x_t of the current time step are inputs of the three gates. The $w_{f,i,o}$ and $b_{f,i,o}$ represent the weight matrix and the deviation vector. The $\tilde{c}_t$ is a candidate state, c_t a cell state, h_t a hidden layer output state, and σ an S-type activation function [9]:

– External input data flows into LSTM neural network and the output data of the upper layer is connected to form input data x_t' = $[h_{t-1},x_t]$. The input data x_t' first flows into the forgetting gate f_t. Calculating the activation function by eq. (1), we obscure the output data of the forgetting gate. The forgetting gate can determine the state information of neurons be cleared.
– The input data x_t' flows into the input gate simultaneously. Calculating the activation function by eq. (2) before getting the output data i_t of the input gate. The input gate is used to determine which information needs to be updated and stored in the storage neuron.
– Pass the input data x_t' to the tan$h$ function. After calculating the activation function by eq. (3), we can harvest the output data $\tilde{c}_t$ of the tan$h$ function, which is a candidate created by the tan$h$ function to update the state data of neurons.

– New state information is generated by updating the old state information c_{t-1} of neurons. New state information c_t is calculated by a function of eq. (4). The candidate vector $\tilde{c}_t$ determines how much state information to update.
– The input data $x_t^{'}$ flows into the input gate simultaneously. After calculating the activation function by eq. (5), the output data o_t of the output gate is obtained.
– In order to process the output data, the activation function is utilized to filter the state information of neurons, and then it is input into the tan*h* function, which is multiplied by the output data o_t of the output gate to obtain the output data $H_t = h_t$.

As for LSTM networks, a gradient descent method is adopted, which propagates from the input layer to the output layer through the hidden layer, and then propagates back to the input layer through the hidden layer in the output layer, thus gradually correcting the connection weight. The optimization strategy is the random gradient descent method Adam, which is a stochastic objective function optimization algorithm based on single-step degree and low-order moment adaptive estimation. Compared with the classical random gradient descent method, it can update the network parameters (weight, deviation) more effectively:

$$g_t = \nabla_\theta f_t\left(\theta_{t-1}\right) \tag{7}$$

$$m_t = \beta_1 m_{t-1} + \left(1-\beta_1\right) g_t \tag{8}$$

$$v_t = \beta_2 v_{t-1} + \left(1-\beta_2\right) g_t^2 \tag{9}$$

$$m_t = \frac{m_t}{1-\beta_1^t} \tag{10}$$

$$v_t = \frac{v_t}{1-\beta_2^t} \tag{11}$$

$$\theta_t = \theta_{t-1} - \alpha \frac{m_t}{\sqrt{v_t} + \epsilon} \tag{12}$$

We set the network parameter to be updated in the process of updating the network weight to θ. Different from the traditional method which updates the parameters in view of the gradient direction of the loss function, Adam introduces the concept of momentum. The followings are specific updating steps:
– the initialized first-order velocity matrix $m_0 = 0$ the estimated second-order velocity moment $v_0 = 0$, and the initialized time step $t = 0$,
– when θ does not converge, repeat the following steps until it converges or reaches the maximum time step,
– under the current time step, according to the eq. (7), the random weight updating direction gt is obtained, and the time step is +1,
– according to eq. (8), mt is updated,
– according to eq. (9), vt is updated,
– according to eq. (10), $\hat{m}_t$ is updated,
– according to eq. (11), $\hat{v}_t$ is updated,
– according to eq. (12), θ is updated.

When the iteration condition of 3rd step is satisfied, the iteration is exited and the update of θ is completed. The α is a learning step, m_t is an estimated first-order velocity moment, v_t is an estimated second-order velocity moment, $\hat{m}_t$ is an estimated first-order velocity moment for deviation correction, $\hat{v}_t$ is an estimated second-order velocity moment for deviation correction, and f_t is a loss function.

According to the introduction of the LSTM neural network model, we believe that this model will have a good fit when describing the above relationship. Besides, there will be a mutual influence between green investment and carbon emissions. In order to get the specific nature of their influence relationship, we will build a basic OLS model to further analyze and explore it.

Basic OLS model

To further explore how the green investment effects carbon emissions, this paper constructs a basic OLS Model 1 for further analysis and research:

$$\ln pollution_{i,t} = \alpha_1 + \beta_1 \ln gi_{i,t} + \delta_1 X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{13}$$

where α_0 represents the constant term in eq. (13), α_1 and α_2 are the coefficient to be estimated of the corresponding variable. The $\ln pollution_{i,t}$ is the explained variable, which represents the result after taking the logarithm of the actual value of carbon emissions. The core explanatory variable is $\ln gi_{i,t}$ that we select the logarithm of the sum of the sum-up investment in pollution control and environmental infrastructure in each province as the measurement index of green investment. The $X_{i,t}$ is a control variable selected to ensure the accuracy and rationality of the research results, including foreign direct investment, science and technology expenditure, urbanization rate, and energy consumption structure. The μ_i is an individual effect and $\varepsilon_{i,t}$ is a random error term.

Data source

Because of the serious data insufficiency in Tibet, Hong Kong and Macao Special Administrations, and Taiwan, 30 provinces nationwide from 2007 to 2019 as research samples are chosen for empirical analysis. The study data are all sourced from the *China Statistical Yearbook*, *China Environmental Statistical Yearbook*, statistical yearbooks of various provinces, CSMAR (China Stock Market & Accounting Research), CNRDS (Chinese Research Data Services), and Carbon Emission Accounts and Datasets (CEADs). See tab. 1 for the representing symbols and calculation formulas of each variable.

Table 1. Representing symbols and measures of variables

Indicators	Symbol	Data calculation formula	Unit
Carbon emissions	*pollution*	Overall carbon emissions	100 million tons
Green investment	*gi*	Completed amount of pollution control investment and environmental infrastructure investment	100 million yuan
Science and technology expenditure	*innovation*	Total amount of science and technology expenditure of provincial governments	100 million yuan
Urbanization rate	*urban*	Urban population/city overall population	–
Foreign direct investment	*FDI*	Amount of foreign direct investment	100 million yuan
Energy consumption structure	*energy*	Total coal consumption/energy consumption	–

Variable description

Explained variable: Total carbon emissions

Here we use the provincial carbon emission data in Carbon Emission Accounts and Datasets (CEADs) to measure this index.

Core explanatory variable: green investment

At present, there are different definitions of green investment without unity for its calculation in the theoretical field. In previous studies, the regional green investment was mostly measured by environmental protection investment. Besides, productive green investments [20] including water conservancy construction investment, forest construction investment, and green enterprise financing were added to reflect the economic benefits of green investment [21]. The research object of this paper is government green investment. Finally, the summed total investment in pollution control and environmental infrastructure construction in each province is selected to measure it.

Control variable

Aiming to control other factors' influence on the regression results between green investment and carbon emissions, as well as ensure the validity and accuracy of the model, we select the following control variables:

- *Science and Technology Expenditure* (*innovation*). This paper uses the science and technology expenditure of local government fiscal expenditure to measure this index. Meanwhile, the degree of technological innovation determines the level of reducing carbon emissions in various places.
- *Urbanization Rate* (*urban*). Urbanization will affect the residents' consumption structure, and then the change in carbon emissions. This paper measures the urban population proportion of each prefecture city.
- *Foreign direct investment* (*FDI*). Which will have an impact on technological progress and then affect carbon emissions [22]. This paper uses the total amount of FDI received by each province to measure this index.
- *Energy Consumption Structure* (*energy*). The ratio of coal consumption to total energy consumption is used to measure this index in this paper, in which coal consumption is constituted from seven related energy terminal consumption and the total energy consumption is constituted from twenty related energy terminal consumption. The coal consumption ratio will affect the changing intensity of carbon emissions and then affect the total carbon emissions [23, 24].

Experimental results and discussion

Descriptive statistical results

Each variable's descriptive statistical results in the regression model are showcased in tab. 2.

In this table, ln*pollution*, ln*gi*, ln*innovation*, ln*urban*, ln*FDI*, and ln*energy* represent the logarithmic results of the original data of total carbon emissions, green investment, science and technology expenditure, urbanization rate, foreign direct investment, and energy consumption structure. In view of above statistics, the standard deviation of the values of the selected variables after taking logarithms is relatively small. To a certain extent, this shows that it is reasonable for us to substitute the logarithmic value into the regression model of eq. (13) to further explore such influence relationship, which can effectively avoid the interference of regional heterogeneity on the experimental results and obtain the overall relationship between green investment and carbon emissions in China.

Table 2. Descriptive statistical results

Variable	Observation value	Mean	Standard deviation	Minimum	Maximum
pollution	390	3409.424	2775.922	249.8279	17000.44
gi	390	87843.2	376087.5	5.5013	2674178
innovation	390	48949.19	173722	3.76	1325155
urban	390	55.23105	13.29098	28.24	89.6
FDI	390	503.7703	722.5075	0.3082	10975.32
energy	390	0.417433	0.1539311	0.0114983	0.724146
ln*pollution*	390	7.846955	0.7814176	5.520772	9.740994
ln*gi*	390	5.414674	2.554002	1.704984	14.79915
ln*innovation*	390	5.344603	3.120343	1.324419	14.09704
ln*urban*	390	3.984172	0.2324387	3.340739	4.495355
ln*FDI*	390	5.341388	1.658265	–1.177006	9.303404
ln*energy*	389	0.9669144	0.499233	–4.11516	–0.3227623

Regression results and analysis

The regression results of the benchmark model can be seen in tab. 3, where:
- indicates the regression relationship between the total green investment and the provincial carbon emission data without adding any control quality,
- indicates the multiple linear regression results after adding control variables, and
- indicates the regression results after adding fixed effects to the original model based on second results.

According to the regression results, green investment has an imperative role in uprising the carbon emissions in 30 prefecture cities in China during the period of 2007 to 2019.

According to the development and goal of carbon emission reduction in China, China proposes to achieve the *carbon peak* and *carbon neutrality* by 2030 and 2060 respectively, which shows that China's current carbon emissions have failed to reach the peak and carbon emissions are still on the rise. Thus, green investment has not yet shown a restraining effect on carbon emissions and the current governmental green investment is still crucial to provincial carbon emissions.

Robustness examination

Aiming to test the robustness of the empirical relationship between green investment and carbon emissions obtained by the above OLS model, following methods are applied to examine its results' robustness.

Systematic GMM estimation: The variable with one-order lag lnpollution is included in the regression Model 13, but the inclusion of the second-order lag variable will cause endogenous problems, which will lead to weak instrumental variables. Therefore, the basic OLS regression model between green investment and carbon emissions is estimated systematically.

Replace data source: This paper replaces the green investment measurement index. The original index GI is the sum of the completed investment in pollution control and the total investment in environmental infrastructure construction. The GI1 is GI plus the completed investment in forestry construction, and GI2 is the total investment in environmental infrastructure removing GI. Add GI1 and GI2 to Model 13, carry out regression, and observe the direction and significance of the regression coefficient of green investment affecting total carbon emissions.

Table 3. Regression results of panel model

	ln*pollution* (1)	ln*pollution* (2)	ln*pollution* (3)
ln*gi*	0.0917***	0.0799***	0.428***
	(0.0148)	(0.0121)	(0.0457)
ln*innovation*	–	–0.0275**	0.0829
	–	(0.00955)	(0.0500)
ln*urban*	–	0.0641	–0.233
	–	(0.187)	(0.168)
ln*FDI*	–	0.210***	0.0413
	–	(0.0218)	(0.0270)
ln*energy*	–	0.820***	0.668***
	–	(0.0728)	(0.0678)
Constant term	7.351***	6.982***	6.454***
	(0.0887)	(0.650)	(0.594)
Amount of samples	390	389	389
Adjustment R^2	0.087	0.471	0.585

Note: ***, **, and * respectively represent 1%, 5%, and 10% as the significance level

We summarize the results of the above two robustness tests in tab. 4.

Table 4. Robustness test results

	ln*pollution* (4)	ln*pollution* (5)	ln*pollution* (6)
ln*pollution*	1.008***	–	–
	(0.0428)	–	–
ln*GI1*	–0.0325	0.449***	–
	(0.0230)	(0.0309)	–
L. ln*innovation*	–0.00462	–0.0380***	–0.0256**
	(0.0106)	(0.00807)	(0.00963)
ln*urban*	–0.454	0.0593	0.106
	(0.295)	(0.158)	(0.186)
ln*FDI*	0.0462*	0.105***	0.213***
	(0.0218)	(0.0203)	(0.0218)
ln*energy*	0.0103	0.427***	0.824***
	(0.112)	(0.0683)	(0.0730)
ln*GI2*	–	–	0.0810***
	–	–	(0.0126)
Constant term	1.668	6.487***	6.749***
	(0.865)	(0.553)	(0.651)
Amount of samples	356	386	389
Adjustment R^2		0.618	0.467

Note: ***, **, and * respectively represent 1%, 5%, and 10% as the significance level

In tab. 4, $\mathrm{L.lnpollution}$ is the total amount of carbon emissions lags by two orders, $lnpollution$(4) represents the result of the GMM estimation test of the system, $\mathrm{lnpollution}(5)$ represents the regression result when using GI1 substitutes GI1 as green investment, and lnpollutio(6) represents the regression result when using GI2 substitutes GI as a green investment. Thus, the results of systematic GMM estimation of the benchmark model between green investment and carbon emissions are robust. In the model containing two lagging carbon emission reduction targets, green investment still has a significant positive effect on total carbon emissions. After increasing or decreasing the data sources of green investment, the estimated results are in line with the regression results of the benchmark model and its robustness is verified.

Summary and prospect

According to the previous analysis and test, we can draw the following conclusions.

- The LSTM neural network model based on governmental green investment and provincial total carbon emission data is feasible when improving the existing model describing their fuzzy relationship, and the feasibility is verified by the regression results of the OLS measurement model constructed by us.
- At the same time, according to the regression results of the OLS model, it can be seen that green investment is beneficial to China's current carbon emissions, which is related to China's current carbon development stage that has not yet reached the carbon peak and carbon emissions are still rising.
- Therefore, in addition to increasing government green investment and rationally arranging budget, it is also suggested that the government should give its full play to carbon emission reduction, focus on pollution control, and improve environmental infrastructure construction in achieving the carbon peak and carbon neutralization.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

References

[1] Juberias, G., *et al*., A New ARIMA Model for Hourly Load Forecasting, *Proceedings*, IEEE Transmission and Distribution Conference, New Orleans, La., USA, 1999, pp. 314-319
[2] Amjady, N., Short-Term Hourly Load Forecasting Using Time-Series Modeling with Peak Load Estimation Capability, *IEEE Transactions on Power Systems, 16* (2001), 4, pp. 798-805
[3] Li, Y. Y., *et al*., Long-Term System Load Forecasting Based on Data-Driven Linear Clustering Method, *Journal of Modern Power Systems and Clean Energy*, 6 (2018), May, pp. 306-316
[4] Christiaanse, W., Short-Term Load Forecasting Using General Exponential Smoothing, *IEEE Transactions on Power Apparatus and Systems, Pas-90* (1971), 2, pp. 900-911
[5] Tao, H., *et al*., A Naive Multiple Linear Regression Benchmark for Short Term Load Forecasting, *Proceedings*, IEEE Power & Energy Society General Meeting, Detroit, Mich., USA, 2011
[6] Chen, B. J., *et al*., Load Forecasting Using Support Vector Machines: A Study on EUNITE Competition 2001, *IEEE Transactions on Power Systems: A Publication of the Power Engineering Society*, 19 (2004), 4, pp. 1821-1830
[7] Mayur Barman, N. B., *et al*., A Regional Hybrid GOA-SVM Model Based on Similar Day Approach for Short-Term Load Forecasting in Assam, India, *Energy, 145* (2018), Feb., pp. 710-720
[8] Kuo, P.-H., *et al*., A High Precision Artificial Neural Networks Model for Short-Term Energy Load Forecasting, *Energy, 11* (2018), 213
[9] Wang, Y., *et al*., Probabilistic Individual Load Forecasting Using Pinball Loss Guided LSTM, *Applied Energy, 235* (2019), Feb., pp. 10-20
[10] He, Y. Y., *et al*., Electricity Consumption Probability Density Forecasting Method Based on LASSO-Quantile Regression Neural Network, *Applied Energy, 233-234* (2019), Jan., pp. 565-575
[11] Zhang, W. J., *et al*., An Improved Quantile Regression Neural Network for Probabilistic Load Forecasting, *IEEE Trans. Smart Grid, 10* (2019), 4, pp. 4425-4434
[12] Li, X., *Et Al*., Forecasting China's Co_2 Emissions For Energy Consumption Based On cointegration approach, *Discret Dyn. and Nat. Soc., 2018* (2018), ID4235076

[13] Martin, P. R., Moser, D. V., Managers' Green Investment Disclosures and Investors' Reaction, *Account. Econ., 61* (2016), 1, pp. 239-254
[14] Campiglio, E., Beyond Carbon Pricing: The Role of Banking and Monetary Policy in Financing the Transition to a Low-Carbon Economy, *Ecol. Econ., 121* (2016), Jan., pp. 220-230
[15] Roc Liao, X., Shi, X., Public Appeal, Environmental Regulation and Green Investment: Evidence from China, *Energy Pol., 119* (2018), Aug., pp. 554-562
[16] Li, Z. Z., *et al*., Determinants of Carbon Emission in China: How Good is Green Investment? *Sustain Product Consumpt*, *27* (2021), July, pp. 392-401
[17] Shen, Y. J., *et al*., Does Green Investment, Financial Development, and Natural Resources Rent Limit Carbon Emissions? A Provincial Panel Analysis of China, *Science of the Total Environment, 755* (2021), 142538
[18] Wang, L., *et al*., How China is Fostering Sustainable Growth: The Interplay of Green Investment and Production-Based Emission, *Environmental Science and Pollution Research International, 27* (2020), 31, pp. 39607-39618
[19] Li, P. Z., *et al*., On the Dynamic Relationship Between Green Finance and Agricultural Carbon Emission, *Journal of Shanxi Radio & TV University, 25* (2020), 02, pp. 101-106
[20] Zhang, M. L., Study of the Spatial Effect of Green Investment in the Process of Marketization for High-Quality Economic Development－Empirical Analysis Based on Space Dubin Model, *Journal of Guizhou University of Finance and Economics*, *70* (2020), 04, pp. 89-100
[21] Yu, T. K., Huang, J. D., Research on the Impact of Green Finance on Carbon Emissions, *Journal of Contemporary Financial Research*, *35* (2022), 1, pp. 57-70
[22] Xu, H. L., Deng, Y. P., Does the Foreign Direct Investment Lead to Environmental Pollution in China? Spatial Measurement Research Based on Inter-Provincial Panel Data in China, *Journal of Management World*, *2* (2012), pp. 36-49
[23] Wang, Q., *et al*., Mechanism of Energy Efficiency Response to Industrial Restructuring and Energy Consumption Structure Change, *Acta Geographica Sinica, 66* (2011), 6, pp. 741-749
[24] Guan, W. H., *et al*., Study on the Change of Energy Consumption Structure in China, *Journal of Natural Resources, 21* (2003), 03, pp. 401-407

Paper submitted: December 1, 2022
Paper revised: January 5, 2023
Paper accepted: January 31, 2023